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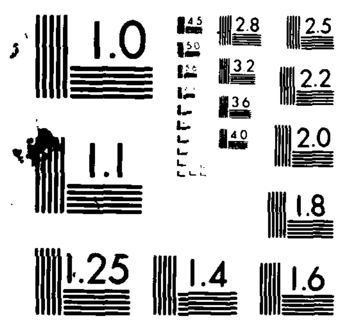

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5 February 1982

Selected Research Opportunities (SRO) II Non-Gaussian Workshop

Papers Presented at the SRO II Non-Gaussian Workshop, 7 and 8 April 1981, NUSC, New London, CT

Office of the Associate Technical
Director for Technology

Naval Underwater Systems Center
Newport, Rhode Island / New London, Connecticut

Preface

This document was prepared by direction of Dr. W. A. Von Winkle, Associate Technical Director for Technology (Code 10), New London Laboratory, Naval Underwater Systems Center. The Selected Research Opportunities (SRO) II Non-Gaussian Workshop was sponsored by NUSC to provide a forum for scientists who are engaged in the ONR Program of Non-Gaussian Signal Processing.

D. M. Viccione, of NUSC (Code 10), and P. L. Stocklin, of Analysis & Technology, coordinated the preparation of this document.

Reviewed and Approved: 5 February 1982

W. A. Von Winkle

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Associate Technical Director
for Technology

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This document presents a record of the subject matter presented and discussed at the first workshop on the ONR Selected Research Opportunities (SRO) III program concerning detection in non-Gaussian noise.

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Selected Research Opportunities (SRO) II Non-Gaussian Workshop, 7 and 8 April 1981 U.S. Naval Underwater Systems Center New London Laboratory, New London, CT

Introduction

by D. M. Viccione
Naval Underwater Systems Center
New London, CT

Conventional acoustic and electromagnetic antisubmarine warfare (ASW) systems are designed to optimally detect the presence of signals in Gaussian background noise. However, in the electromagnetic environment (EM) high level directional transient or other *structured* noise is a familiar problem. Such interferences are typically non-Gaussian. Frequently receiver systems designed for Gaussian noise backgrounds are seriously degraded in the non-Gaussian environment. During the past 5 years, considerable attention has been focused on the (1) problem of characterizing non-Gaussian noise fields and (2) design of EM detectors (receivers) that operate optimally in such environments.

The necessity of operating acoustic surveillance and communication systems in typical non-Gaussian noise backgrounds must be anticipated. Such noise may arise naturally from, for example, oil exploration and drilling in the deep sea, or deliberately from intentional jamming, such as detonations of high-yield explosives in ocean basins.

The Office of Naval Research (ONR) has initiated a new feature, the Selected Research Opportunities (SRO) Program, in its Contract Research Program (CRP). The SRO Program, like the CRP, is designed to further the goal of improved national defense over the long term. This is to be accomplished through (1) increased involvement of the academic research community in selected fundamental research areas and (2) fostering stronger links between this community and the Navy. One of the research areas in the SRO Program is that of non-Gaussian signal processing, which offers an opportunity to explore the feasibility and practicality of designing and developing ASW systems to operate efficiently in non-Gaussian noise. Generically the issues to be resolved by the non-Gaussian research give rise to the following objectives:

1. To analyze existing algorithms for *worst case* situations in the presence of intentional man-made noise. Nonparametric and robust approaches should be explored to devise algorithms that perform well regardless of noise source characteristics.

2. To investigate techniques for weak signal extraction in the presence of strong signals; and, as a special case, explore techniques for detecting spread-spectrum signals, including analysis of changes in noise statistics caused by pseudo-noise signals.

3. To enlarge the basic mathematical and statistical theory of non-Gaussian stochastic processes applicable to EM and underwater sound environments.

4. To study non-Gaussian models appropriate for reverberation or reverberation-like noise in shallow water.

5. To examine the extent of non-Gaussian sources of impulsive noise interference in underwater acoustic signal processing problems of interest to the Navy.

6. To overcome shortcomings in existing theories concerning nonwhite interference, nonstationarity of channels and interferences, multipath, dispersion, Doppler effects, and problems caused by sensor and array flaws.

The workshop, jointly sponsored by ONR and the Naval Underwater Systems Center (NUSC), was the first to bring together SRO II participants and others in the processing community who are working in the area of non-Gaussian noise. Summaries of each technical presentation are provided in this document and a list of participants is included to facilitate communication. The schedule for the presentation of the papers at the SRO-II Workshop, held on 7-8 April 1981 at NUSC New London, CT, follows.

Schedule of the SRO II Non-Gaussian Workshop

Tuesday, 7 April

0900	Welcome	W. A. VonWinkle (NUSC)
0915	Introductory Address	E. G. Wegman (ONR)
0930	The Performance and Robustness of Suboptimum and Locally Optimum Detectors in Non-Gaussian Noise	A. D. Spaulding U.S. Dept. of Commerce (NTIA)
1015	Non-Gaussian Interference Environments, State of the Art Remarks	D. Middleton Consultant
1100	Performance of the Optimum and Several Suboptimum Receivers for Threshold Detection of Known Signals in Additive, White, Non-Gaussian Noise	R. F. Ingram (NUSC)
1300	Frequency Tracking and Parametric Spectrum Analysis	L. Scharf (Colorado State University)
1330	Non-Gaussianity of Oceanic Internal Waves	D. McClovic (Arreté Assoc)
1400	Discussion	

Wednesday, 8 April

0830	Acoustic Problems	R. F. Dwyer (NUSC)
0900	Data-Adaptive Principal Component Signal Processing	D. W. Tufts (University of Rhode Island)
0930	Residual Signal Analysis --A Search and Destroy Approach to Spectral Analysis	J. P. Costas (General Electric Company)
1015	Optimal Identification of Nonlinearly Transformed Gaussian Processes	C. L. Hindman (TRW Systems)
1100	General Discussion	

The Performance and Robustness of Suboptimum and Locally Optimum Detectors in Non-Gaussian Noise

by A. D. Spaulding
U.S Dept. of Commerce (NTIA)
Boulder, CO

Most currently used receiving systems are those that are optimum in Gaussian noise. Unfortunately, the actual interference environment is almost never Gaussian in character, but usually quite different, being *impulsive* in nature. By impulsive, we mean that there are small probabilities of quite large instantaneous values of noise. This is a general definition in that there exist both broadband (the usual definition) and narrowband impulsive processes. When confronted with this real-world interference, the usual procedures were to attempt to *change the interference*, as seen by the receiver, to look more Gaussian in character. Such attempts usually employed various ad hoc nonlinearities preceding the detector. While these are occasionally reasonably effective, they can be extremely wasteful of spectrum space when *normal* signal-to-noise ratios are considered. As we will see, these ad hoc nonlinearities can, under certain conditions, be *almost as good* as the optimally derived nonlinearity for the limiting case of a vanishing small signal. (It is believed that this result may, however, be misleading and it requires further investigation.)

Only recently have there been receiving systems designed to match the actual interference. These truly optimum systems are usually difficult to realize physically. It is possible, however, if the desired signal is small, to obtain realizable systems that approach true optimality. These are generally termed *locally optimum*. The receiving systems must be adaptive, adjusting themselves to changing interference conditions. That is, they must estimate the appropriate parameters for the noise models from which the system was designed. The design is usually done by techniques termed *locally optimum Bayes detection* (LOBD). The parameter estimation problem is currently being investigated via locally optimum Bayes estimation (LOBE) [Middleton (to be published)].

It is the purpose of this presentation to investigate the *robustness* of these locally optimum systems. That is, we want to determine the degree of accuracy required in the parameter estimation procedure. For illustration we will use, initially, two examples of interference, one broadband and one narrowband, and consider the simplest case of coherent signal detection. The standard LOBD analysis is reviewed and then used to determine the performance for arbitrary interference with the detector that is locally optimum for any given interference (our estimate). Of course, if the actual interference and the estimate are identical, we obtain the standard results. Next, we study in some detail the two most common ad hoc nonlinearities (the hard-limiter and the adaptive clipper) to determine their *small signal* performance via the LOBD results. Then, we present a series of sample calculations comparing the performances of the hard-limiter and LOBD nonlinearities and the robustness (for the narrowband noise example) of the LOBD nonlinearity. It is suggested that the small signal limiting results, in some cases at least, may be misleading. We show this by presenting some system performance results that seem to be contrary to the limiting results (which are obviously true) when small (but nonzero) signal levels are considered.

The LOBD analysis employed to obtain the robustness results and the comparison of performance between LOBD's and various nonlinear ad hoc detectors requires use of the central limit theorem and are strictly valid only as the signal becomes vanishingly small. In special cases, the broadband interference model utilized (Middleton's Class B Noise Model) reduces (approximately) to the mathematically simpler Hall Noise Model. The analysis is repeated for the Hall model and performance estimates are obtained for the LOBD and hard-limiter without resorting to the vanishingly small signal assumption. It is shown that performance results obtained via the vanishingly small signal assumption are valid, at least for the special cases considered, as long as the time-bandwidth product is reasonably large (> 30).

Non-Gaussian Interference Environments, State-of the-Art Remarks

by D. Middleton
128 East 91st St.
NY, NY

An overview of recent work by the author on non-Gaussian noise models and threshold signal processing involving non-Gaussian electromagnetic interference (EMI) is presented here. The principal purpose is to offer a technical update of results obtained recently, with some of their implications for a quantitative description of the EMI environment pertinent to Navy uses. Both acoustic and EM applications would be included. Although a complete overview is not made or intended, various specialized interests should find appropriate topics of interest without difficulty.

The current material is compiled from a series of recent presentations by the author (1980, 1981) in the form of vugraphs. The main topics are

1. construction of analytically tractable non-Gaussian noise models,
2. optimum threshold detection algorithms for non-Gaussian EMI environments, and
3. evaluation of optimum and suboptimum receiver performance.

The suboptimum receivers considered are optimum in Gaussian noise (e.g., correlation detectors that are seen to be very much degraded in highly non-Gaussian environments). Finally, the critical role of the EMI scenario is discussed, whereby the parameters of the noise model may be constructed from statistical-physical consideration and measured empirically.

Performance of the Optimum and Several Suboptimum Receivers for Threshold Detection of Known Signals in Additive, White, Non-Gaussian Noise

by R. F. Ingram
Naval Underwater Systems Center
New London, CT

The additive noise encountered at a receiver input is often non-Gaussian. If the non-Guassian nature of the noise is taken into account in the design of the receiver, significant performance improvements relative to the performance of the linear receiver can be achieved. This presentation discusses the performance improvements that can be expected from the optimal and several subpotimal receivers frequently utilized for detecting known threshold signals in an additive, white, non-Gaussian noise.

One form of the optimum receiver for detecting known threshold receivers in additive, white, non-Gaussian noise consists of the receiver that should be utilized if the noise were Gaussian, except that a nonlinearity is placed between the receiver input and the Gaussian detector. The input-output characteristic of the nonlinearity is given by -d/dx(1n p(x)), where p(x) is the 1st order probability density function of the noise alone. The measure of performance improvement obtained by including the nonlinear device is given by the ratio of the signal-to-noise ratio (SNR) at the receiver output with and without a nonlinear processor. The magnitude of this improvement for threshold signals is evaluated using the 1st order probability density functions resulting from Middleton's Class B Noise Model. The performance of several suboptimal but more easily implemented nonlinearities, i.e. clipper, hole puncher, and hard limiter, are also evaluated and compared to the optimal's performance. Finally the performance of these threshold receivers are evaluated as a function of the receiver input SNR.

Frequency Tracking and Parametric Spectrum Analysis

by L. Scharf
Colorado State University
Department of Electrical Engineering
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In this presentation we review several key ideas in random phase tracking, parametric spectrum analysis, and prediction in infinite variance random processes. It is shown that random phase- and frequency-modulated data may be tracked with a dynamic programming algorithm that recursively maximizes Bayesian recursions to generate surviving sequences that ultimately can qualify as maximum likelihood sequences. The discussion of parametric spectrum analysis focuses on a parameterized version of the Bartlett and maximum likelihood spectra, and the performance that can be expected. The discussion of prediction in infinite variance processes deals with procedures for constructing predictors and whiteners when no finite prediction error variance is available for minimization.

Non-Gaussianity of Oceanic Internal Waves

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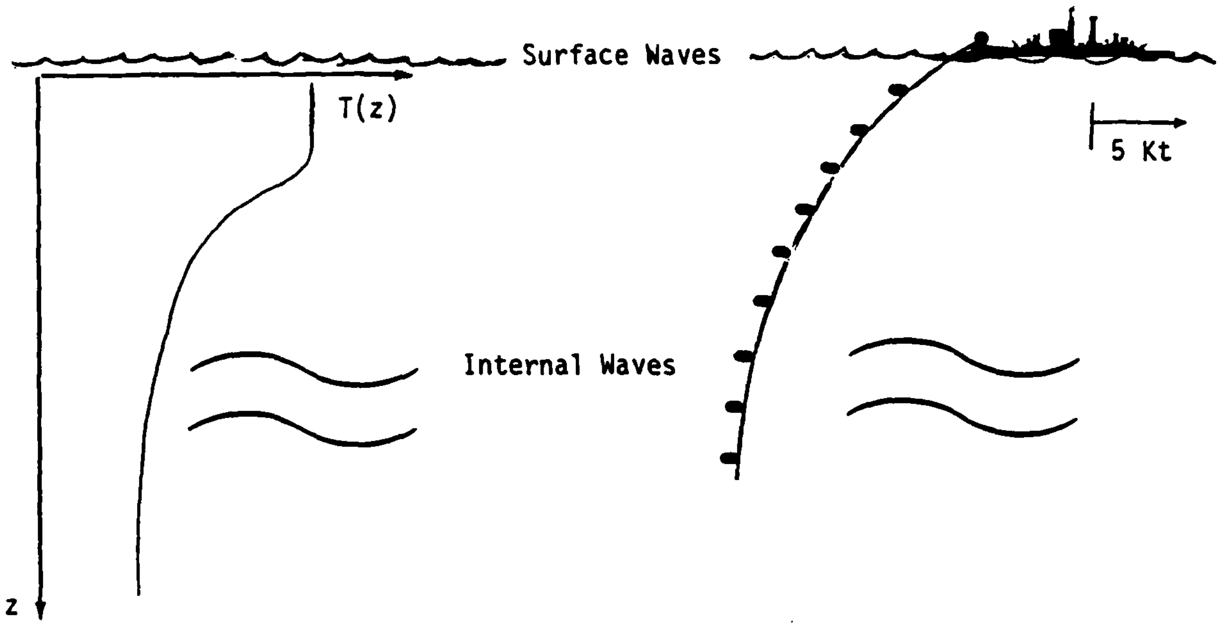
Introduction

The background noise field of concern is the ambient field of internal waves and sporadic turbulence. The horizontal scales of these phenomena range from tens of kilometers to less than the present instrumentation limits (centimeters). The natural fluctuations in the environment can be conveniently characterized in the form of 1-D and 2-D displacement spectra.

One-dimensional horizontal displacement spectra obtained at different times and places in the seasonal thermocline consistently have slopes between -2 and -2.5, with the latter being more common on the scale of 4-10 m. When the spectral estimates are averaged over a large (~10 km) horizontal extent in a given locale, they exhibit apparent stability and approximate universality. However, the spectral levels can vary considerably over horizontal scales of 500 m, even when the data from many sensors are averaged. Two-dimensionsl displacement spectra have been estimated from thermistor chain tows and the spectral shapes are in agreement with the McClovic model, i.e.,

$$[\zeta^2] \sim C\, k_x^{-\frac{5}{2}} \left(k_x^2 + k_z^2\right)^{-1/2} .$$

Examples of the spectra are given in the following figures.



Estimate internal wave displacement from temperature fluctuations $T_i(x)$:

$$d_i(x) = \frac{T_i(x) - \langle T_i \rangle}{\langle dT/dz \rangle_i}$$

$$\langle dT/dz \rangle_i = \frac{\langle T_{i+m} - T_{i-m} \rangle}{z_{i+m} - z_{i-m}}$$

Figure 1. Oceanic Internal Waves

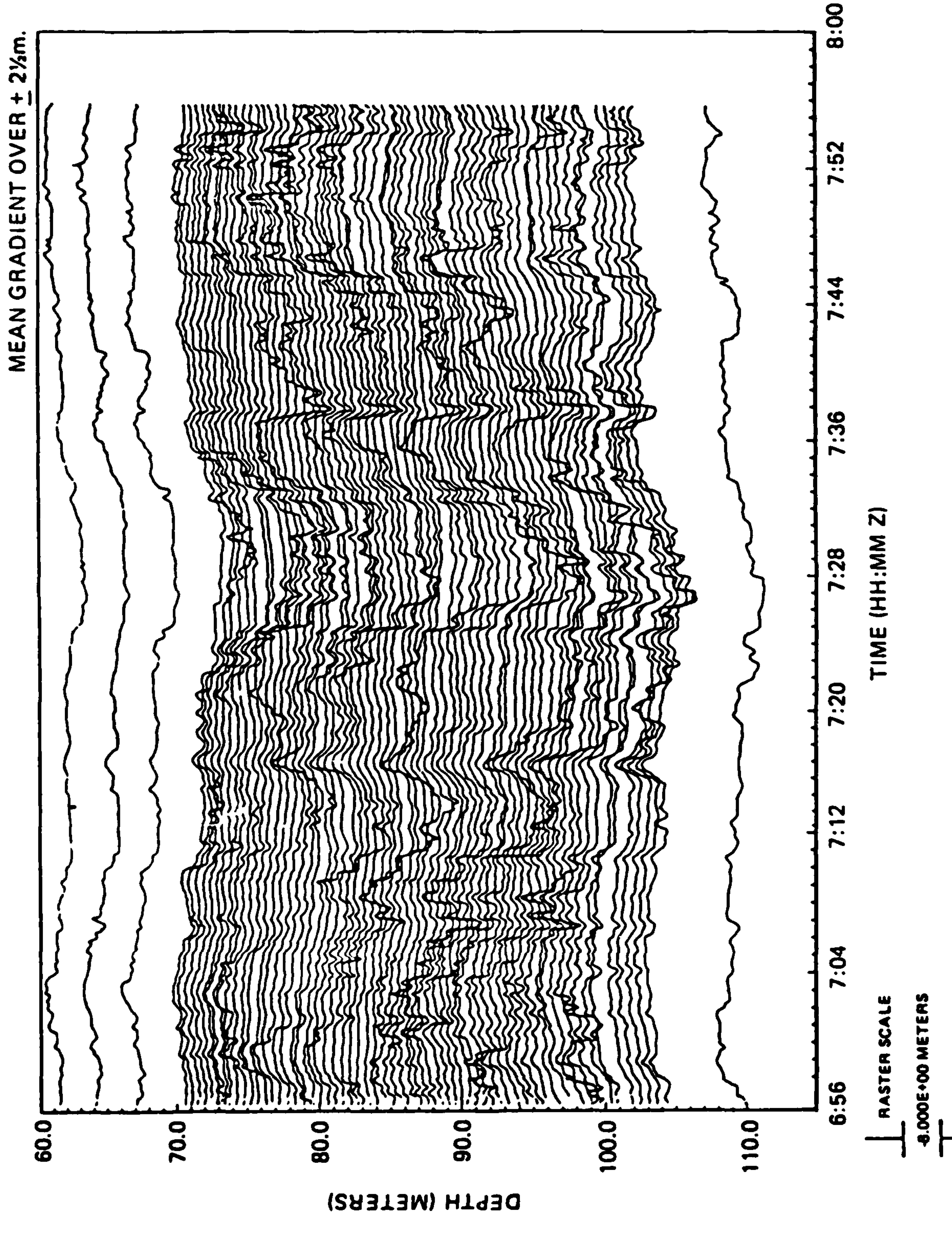


Figure 2. Temperature Displacement Raster

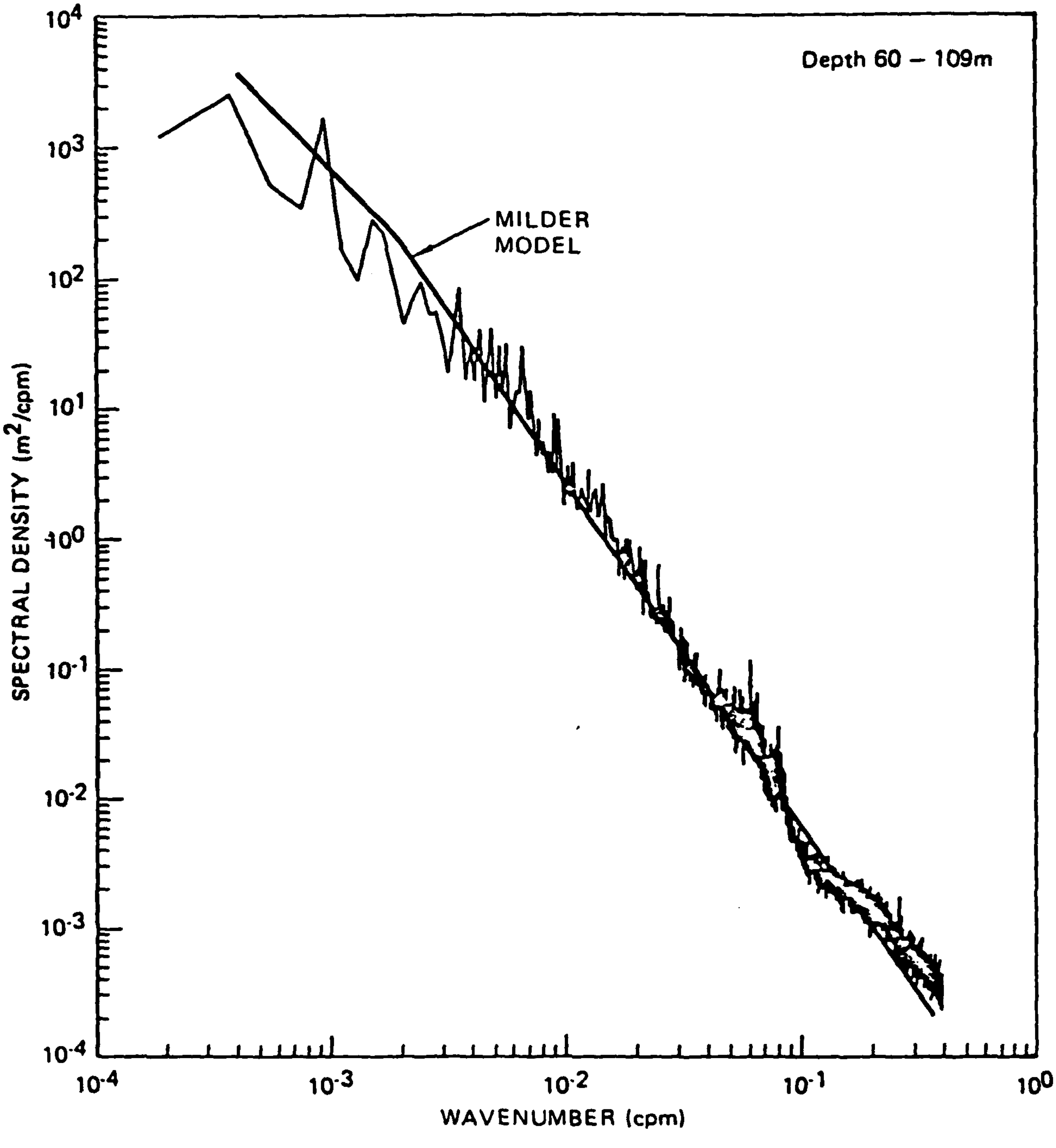
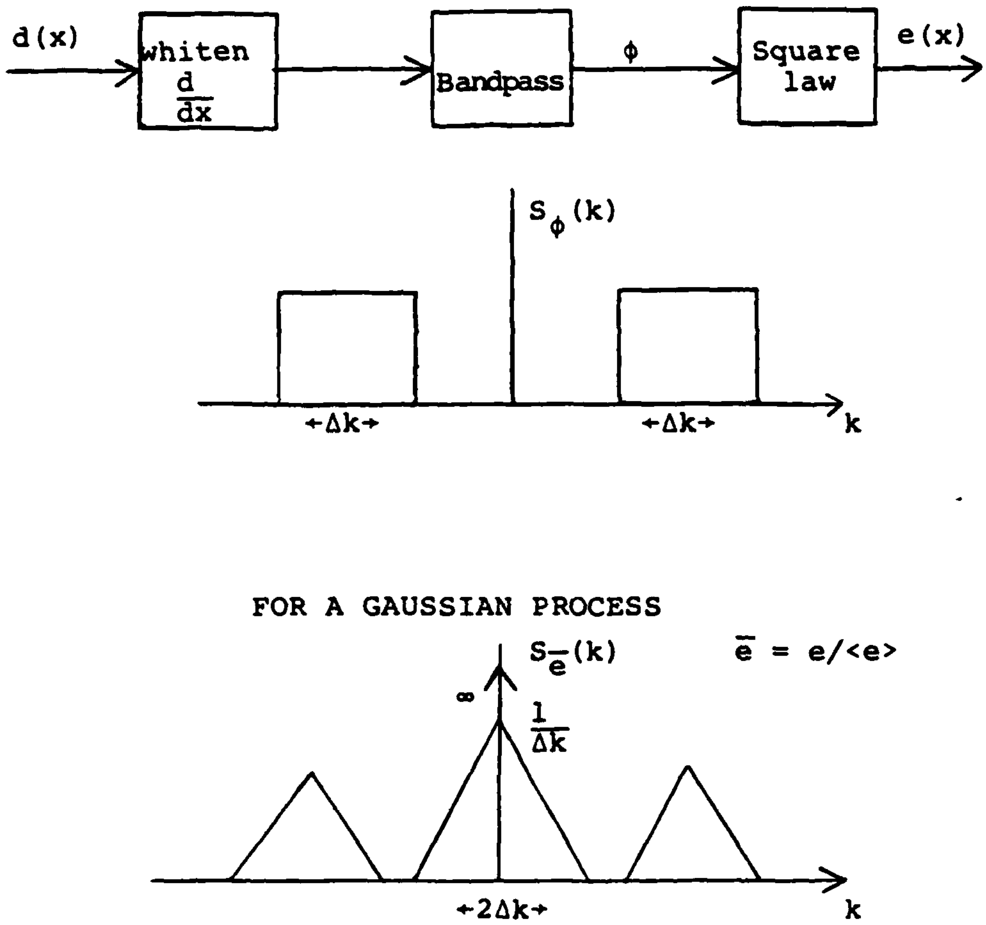


Figure 3. Average Horizontal Power Spectrum of Temperature Displacement Data (Horizontal Data Patch of 5.26 km; Sample Interval of 1.28 m)



and in particular

$$\lim_{k \to 0} S_{\bar{e}}(k) = \frac{1}{\Delta k}$$

Figure 4. Test for Gaussianity by Looking at Higher Order Moments

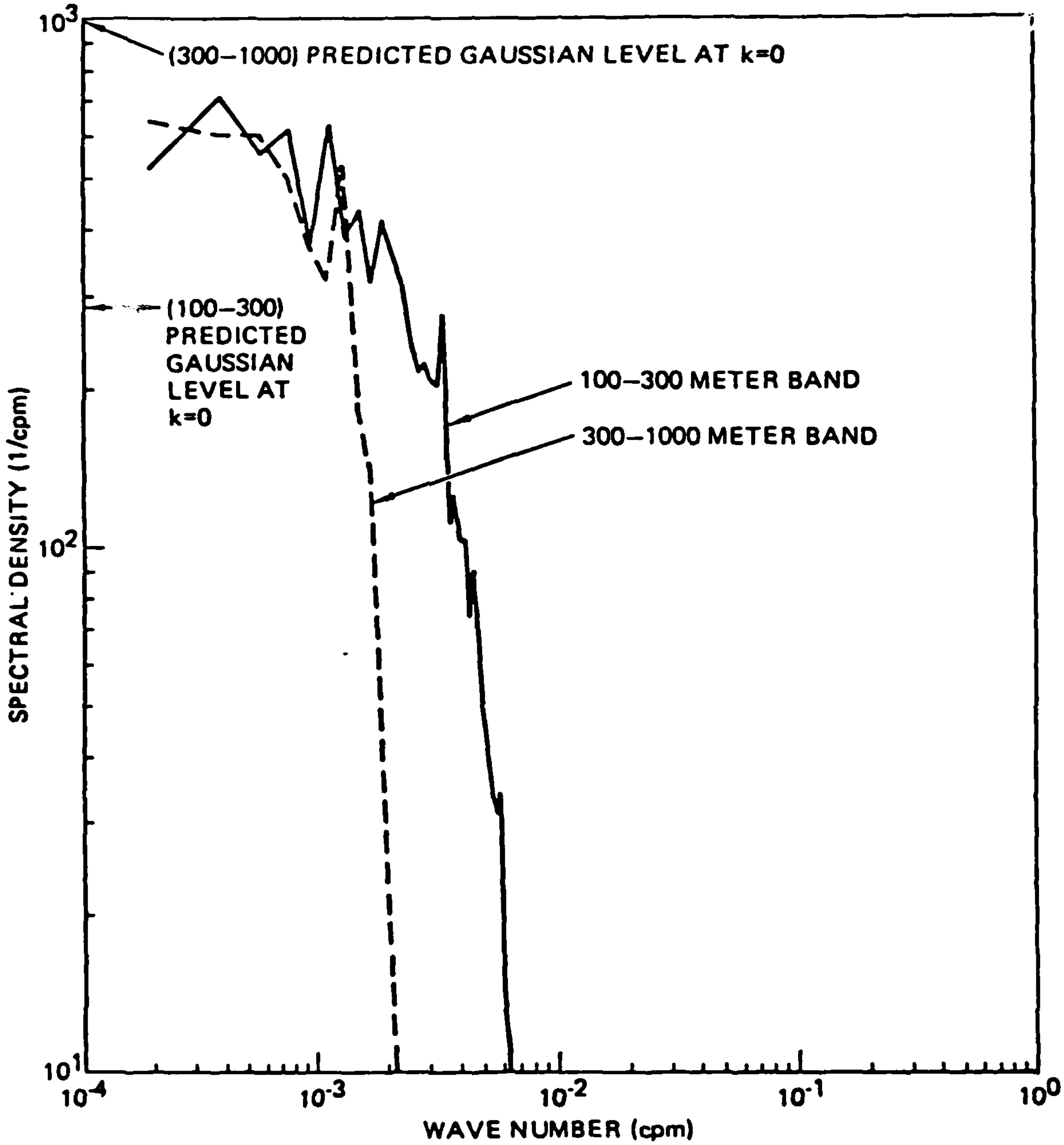


Figure 5. Spectral Density for the Normalized, Whitened, Bandpassed Power Average Over Depth (100-1000 m Band)

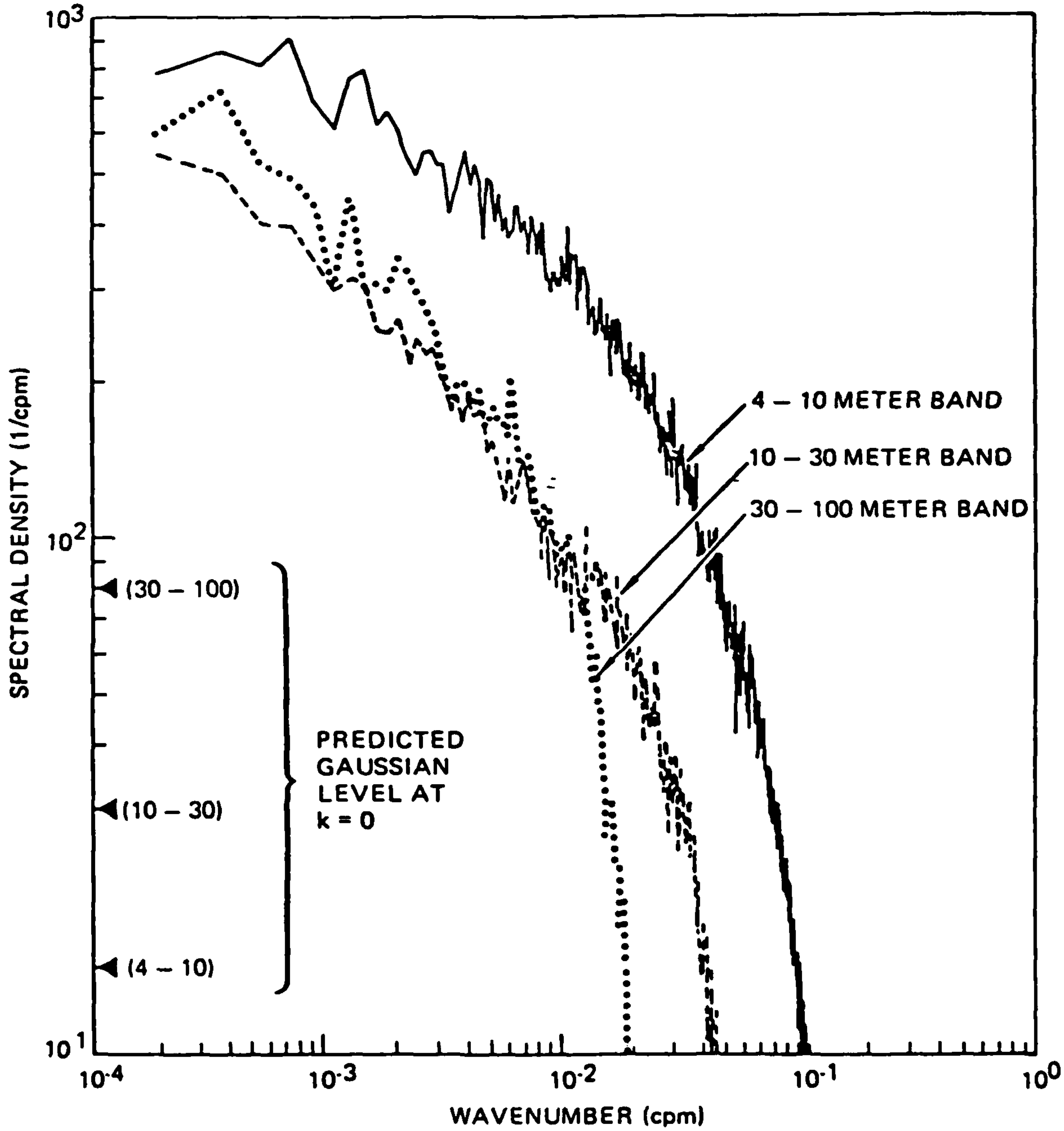


Figure 6. Spectral Density for the Normalized, Whitened, Bandpassed Power Averaged Over Depth (4-100 m Band)

Approach

A model has been formulated to account for the large fluctuation observed in the displacement data. In particular, a nonlinear temperature profile is used to account for the degree of non-Gaussianity observed in the temperature fluctuations, presuming that the internal wave field is Gaussian.

The temperature model is described as follows (see figure 7):

$$T(x,z) = T_o(x, z - \zeta(x,z)),$$

with T_o and ζ Gaussian processes

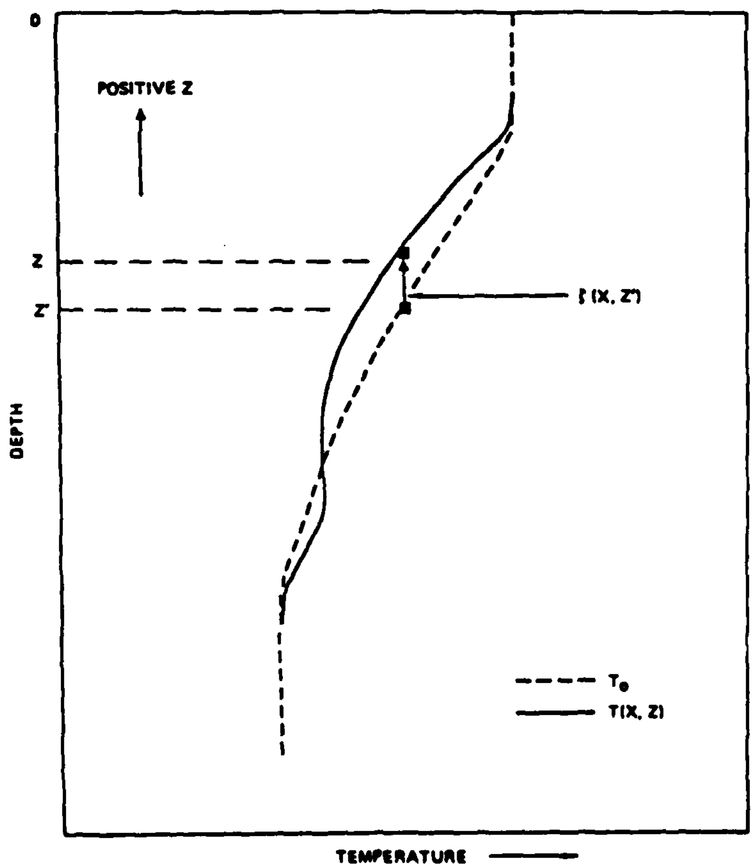


Figure 7. Temperature Model

$$T(x,z) = T_o(x, z - \zeta(x,z))$$

Look at the whitened temperature:

$$\frac{\partial T}{\partial x} = \frac{\partial T_o}{\partial x} - \frac{\partial T_o}{\partial z} \frac{\partial \zeta}{\partial x}$$

Define deviation from linearity

$$\frac{\partial T_o}{\partial z} = \left\langle \frac{\partial T_o}{\partial z} \right\rangle (1 + \theta), \quad \text{so that}$$

$$d'(x) = \left\langle \frac{\partial T}{\partial z} \right\rangle^{-1} \frac{\partial T_o}{\partial x} + (1 + \theta)\zeta'$$

High pass d': $d' \rightarrow d_s'$

$$d_s' = (1 + \theta_L(x, z-\zeta))\zeta_s' + (\theta_s \zeta')_s$$

where

$$\theta = \theta_L + \theta_s.$$

Look at the effect of long scales in θ on the non-Gaussianity of short scale fluctuations d_s'

$$d_s'(x) = [1 + \theta_L(x)]\zeta_s'(x)$$

assuming $\theta_L \zeta_s'$ Gaussian with PSD $P_\theta(k)$, $P_\zeta(k)$.

THE STATISTICS OF DISPLACEMENT POWER

Definition

$$e(x) \equiv d_f^{\,2}(x) = [1 + \theta(x)]^2 \, \zeta_f^{\,2}(x)$$

$$\bar{e} \equiv e(x)/\langle e\rangle$$

Mean

$$\langle e\rangle = \int_{k_1}^{k_2} P_{d_f}(k)\, dk = [1 + \langle\theta^2\rangle]\, \langle\zeta_f^{\,2}\rangle = [1 + \langle\theta^2\rangle] \int_{k_1}^{k_2} P_\zeta(k)\, dk$$

Variance and Covariance (θ, ζ Gaussian)

$$\mathrm{Var}[e(x)] = \langle\zeta_f^{\,2}\rangle^2 \, [2 + 16\langle\theta^2\rangle + 8\langle\theta^2\rangle^2]$$

$$\mathrm{Cov}[\bar{e}(x)] = \frac{2\,\mathrm{Cov}^2[\zeta_f]}{\langle\zeta_f^{\,2}\rangle} + \frac{4\,\mathrm{Cov}[\theta] + 2\,\mathrm{Cov}^2[\theta]}{1 + 2\langle\theta^2\rangle + \langle\theta^2\rangle^2} + \left\{\frac{2\,\mathrm{Cov}^2[\zeta_f]}{\langle\zeta_f^{\,2}\rangle}\right\}\left\{\frac{4\,\mathrm{Cov}[\theta] + 2\,\mathrm{Cov}^2[\theta]}{1 + 2\langle\theta^2\rangle + \langle\theta^2\rangle^2}\right\}$$

Normalized Power PSD

$$P_{\bar{e}}(k) = F(A) + F(B) + F(A) * F(B)$$

$$F(A) = \frac{2\int P_{\zeta_f}(k')\, P_{\zeta_f}(k-k')\, dk'}{\left[\int_{k_1}^{k_2} P_{\zeta_f}(k')\, dk'\right]^2}$$

$$F(B) = \left[1 + 2\langle\theta^2\rangle + \langle\theta^2\rangle^2\right]^{-1} \left[4\, P_\theta(k) + 2\int P_\theta(k')\, P_\theta(k-k')\, dk'\right]$$

A REPRESENTATIVE EXAMPLE
(Note: Two-Sided Spectra)

Filtered Internal Wave Horizontal Spectrum = Ak^{-2}

$$P_{\dot{\zeta}_f}(k) = (2\pi)^2 A : (k^* < k_1 < |k| < k_2) \Rightarrow F(A) \approx \frac{1}{\Delta k}\left[1 - \frac{|k|}{\Delta k}\right] : (|k| << k_1)$$

$$P_\theta(k) = \frac{<\theta^2>}{2\,k_\theta} : (|k| < k_\theta < k_1) \Rightarrow F(B) \simeq \frac{4\,\frac{<\theta^2>}{2\,k_\theta} + 2\left(\frac{<\theta^2>}{2\,k_\theta}\right)^2 \left[2k_\theta - |k|\right]}{1 + 2<\theta^2> + <\theta^2>^2} : (|k| < 2k_\theta)$$

Spectrum for Normalized Power

$$\boxed{P_{e/<e>}(k) = \frac{1}{\Delta k}\left\{1 + G_1\left(<\theta^2>, \frac{\Delta k}{k_\theta}\right)\right\} + \frac{1}{k_\theta}\,G_2(<\theta^2>) - \frac{|k|}{(\Delta k)^2}\left\{1 + G_3\left(<\theta^2>, \frac{\Delta k}{k_\theta}\right)\right\}}$$

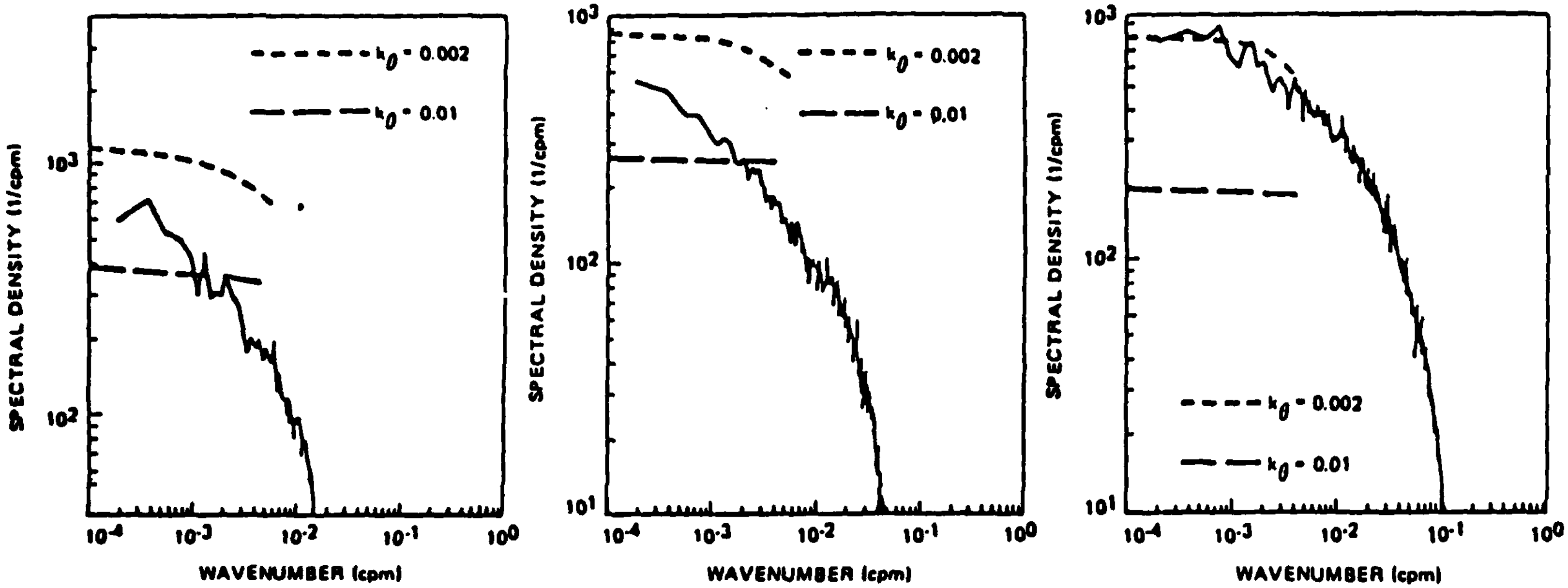
where

$$G_1\left(<\theta^2>, \frac{\Delta k}{k_\theta}\right) = \frac{8<\theta^2> + 2<\theta^2> - \frac{k_\theta}{\Delta k}\left(8<\theta^2> + \frac{4}{3}<\theta^2>^2\right)}{1 + 2<\theta^2> + <\theta^2>^2}$$

$$G_2(<\theta^2>) = \frac{2<\theta^2> + <\theta^2>^2}{1 + 2<\theta^2> + <\theta^2>^2}$$

$$G_3\left(<\theta^2>, \frac{\Delta k}{k_\theta}\right) = \frac{\frac{\Delta k}{k_\theta}\left(2<\theta^2> + <\theta^2>\right) + \frac{1}{2}\left(\frac{\Delta k}{k_\theta}\right)^2 <\theta^2>^2}{1 + 2<\theta^2> + <\theta^2>^2}$$

Gaussian Prediction If $G_1 = G_2 = G_3 = 0 \rightarrow <\theta^2> = 0$



3-1a $P_\theta(k)$ of Towed Temperature Displacements for the 30 – 100m Waveband.

3-1b $P_\theta(k)$ of Towed Temperature Displacements for the 10 – 30m Waveband.

3-1c $P_\theta(k)$ of Towed Temperature Displacements for the 4 – 10m Waveband.

Figure 8. The Spectral Density of the Power of Normalized, Whitened, Bandpassed Temperature Displacements (The spectra are ensembles of 70 individual cases covering 40 m in depth. The horizontal extent of the data is 5.26 km; the sample interval is 1.28 m. Predictions of the power spectral levels from the microstructure model are included for two values of k_θ with $< \theta^2 > = 1$.)

Acoustic Problems

by R. F. Dwyer
Naval Underwater Systems Center
New London, CT

This presentation describes the results of a statistical analysis study of FRAM II Arctic under ice ambient-noise data. The specific data analyzed were recorded on 23-24 April 1980 from a pack-ice camp in the Arctic Ocean at 86° N latitude, 25° W longitude. At this location, the bottom depth was approximately 4000 m. The measurement system consisted of a broadband omnidirectional hydrophone suspended to a depth of 91m from a sonobuoy located in a lead. Under the influence of Arctic currents, the pack ice was slowly moving. This movement caused rifting and cracking of ice that occurred, at times, throughtout the experiments and represented a structured acoustic noise source. Both impulsive and burst noises were identified in the data and were probably caused by tensile cracks and rubbing ice masses.

To better understand the statistical properties of under ice ambient noise, the skew, kurtosis, and cumulative distribution function (CDF) of the data were estimated. In the time domain, the statistics were estimated in 100-, 350-, and 2500-Hz bands. At times, the statistical estimates in all bands deviated from Gaussian noise significantly, and were consistent with previously reported results of experiments made in the Canadian Arctic Archipelago. The estimated energy CDF of FRAM II data predicted detection thresholds 3 to 10 dB higher than what would be expected from purely Gaussian phenomena. Spectrum levels and spectrograms were also measured. The spectrograms depicted dynamic frequency components that appear, from aural information that sounded like squeaks, to be correlated with ice dynamics. Comparisons of broadband spectrum level estimates at different times, indicate nonstationary frequency domain components that also appear to be correlated with ice dynamics.

Since it was known that burst-noise durations of Arctic under ice noise last from 0.1 to 1/3 s, statistical estimates of frequency domain components were measured. These frequency domain statistical measurements represent new techniques for estimating environmental noise phenomena. The complex skew, kurtosis, and CDF were measured in 1-, 2-, 6-, and 10-Hz resolution cells at the output of a discrete Fourier transform, employing processing times of 2 to 14 min. These new findings indicate the existence of strong non-Gaussian noise in the frequency domain.

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Data-Adaptive Principal Component Signal Processing

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Department of Electrical Engineering
University of Rhode Island
Kingston, RI

Even the best linear-prediction-based methods for fitting multiple-sinusoid signal models to observed data, such as the forward-backward methods of Nuttall (reference 1) and Ulrych and Clayton (reference 2), are ill-conditioned. The locations of estimated spectral peaks can be greatly affected by additive noise. This ill-conditioning can be alleviated by singular value decomposition of the linear-prediction-data matrix. (This is a preliminary version of a presentation to be made at the First ASSP Workshop on Spectral Estimation, 17-18 August 1981, McMaster University, Hamilton, Ontario.)

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Residual Signal Analysis--A Search and Destroy Approach to Spectral Analysis

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A signal processing procedure especially suited for use in narrowband spectral analysis or *line tracking* applications is presented. A modular approach is employed that permits each tracker to optimize estimation parameters for the line assigned. The signal estimate from each module is used to cancel the corresponding signal from the common bus to which all tracker inputs are connected. A *feedback* arrangement around each module restores to each tracker the full level of its assigned input signal. Thus, each signal being tracked is prevented from causing interference to any other tracker. The advantages obtained from this arrangement are demonstrated and discussed.

Optimal Identification of Nonlinearly Transformed Gaussian Processes

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In a variety of applications it is necessary to deal with observations of a time series obtained via an instantaneous nonlinear mapping of an underlying random variable whose values cannot otherwise be ascertained. In the case where the nonlinear mapping is known and can be unambiguously inverted, such a complication represents little difficulty. However, in some applications, a priori knowledge of the intervening nonlinear mapping is either incomplete or altogether lacking. In such cases any analysis of the underlying random process must be accompanied by the identification or, more correctly, the estimation of one or more features of the nonlinear map or measurement function itself.

This presentation is concerned with the practicalities of this identification problem in the case where the underlying random process is Gaussian or, rather, Gauss-Markov in nature and generally exhibits strong serial or time correlation. It is this factor of time correlation that renders the procedures discussed herein of interest, for in the case of independent observations the determination of the nonlinear map is essentially equivalent to the estimation of the univariate density junction of the observations themselves. In the serially correlated case, however, the most efficient use of the observations will involve simultaneous estimation of the nonlinear function, as well as the structure of the correlation of the underlying process. In this sense the procedure advocated here may be regarded as a general scheme for fitting nonlinear time series models, albeit the nonlinearity is of a rather restricted type. A few practical circumstances in which the procedure discussed may be of value are indicated briefly as follows:

1. *Measurement by a sensor of unknown characteristic.* When the response of a sensor is unknown, but one has available sensor measurements of an underlying random process of known character, then we are confronted with the problem of identifying both the sensor and estimating the underlying processes simultaneously; i.e., if y is the sensor output we have

$$y(t) = h(x(t)), \tag{1.1}$$

where h(x) is the sensor response to be determined from the measurements y(t).

2. *Indirect determination of internal motion via measurement of an imbedded scalar in a stratified medium.* To trace the dynamic development of the local fluid vertical velocity in the thermally stratified atmosphere by means of a time series temperature measurement at fixed altitude, we hypothesize the measurement relation

$$T(t) = T_0\left\{Z - \int^t w(t)dt\right\}, \tag{1.2}$$

where T(t) is the recorded time series of temperature, Z is the sensor altitude, w(t) is the instantaneous vertical fluid velocity at measurement altitude Z, and T(h) is the equilibrium or ambient thermal lapse or profile as a function of altitude, which is to be regarded as unknown except through the measurements T(t).

3. *Measurement of concentration fluctuations of reactive species.* When two or more chemically reactive species are randomly distributed in a medium, the equilibium concentration of species A,C_A and another species B,C_B may be related via an equilibrium equation of the form

$$C_A = f(C_B, \theta),$$

where θ is a set of unknown or incompletely known parameters. When, for instance, knowledge of C_B is desired, but C_A is more conveniently measurable, then we must invert the nonlinear relationship to obtain the C_B fluctuation history.

4. *Nonlinear time series modeling.* In some instances it is useful to simply assume the existence of an instantaneous functional relationship between an observed series and an underlying hypothetical series even when no justifiable basis for such a transformation can be advanced. Such ideas are proposed frequently in the analysis of economic time series when it is desired to transform a given series into one that possesses more desirable characteristics from the analyst's point of view.

The common underlying feature of these examples is the necessity of determining the structure of the nonlinear measurement relation. This is done, more or less, on the basis of the observations alone in the absence of a priori detailed information concerning the statistics of the underlying process that generated the measurements in the first place (e.g., the spectrum or covariances). Since the problem of determining both the nonlinear transformation and the underlying realization is highly nonunique, we expect that useful results will be obtainable only when the form, the general structure, or the probability distribution of the underlying process can be regarded as given at least approximately. Such will be the assumption made throughout this presentation; however, we make the observation that, just as the maximum likelihood estimation of linear Gaussion time series model parameters has a least squares interpretation even for non-Gaussion distributions, we expect similar utility and robustness in the present context. This will be true even when the underlying distribution is not known, so long as minimization of the residual sum of squares leads to adequate estimation of the covariance structure.

The basic assumptions concerning the nonlinear mapping to be made are of concern, and here we are guided by practice and intuition. The required basic features are uniqueness and smoothness. By uniqueness we mean that the measurements are related to the underlying process in a one to one fashion over the range of actually observed values. Of course, maps of a more complex structure could be treated if additional a priori information were available.

Requisite properties of smoothness are somewhat more difficult to define precisely. Certainly for discrete parameter data the empirical sampling density of the observations as a function of the observed value must be assumed to be such that variations of the inverse map $g(y) = x$ ($y = h(x)$) are not severely aliased if the behavior of $g(y)$ is to be adequately discerned from the data on hand. For the actual computational implementation considered, we use the stronger assumption of continuous piecewise linearity; although in some applications this assumption may be inappropriate. However, it will emerge that this assumption provides considerable computational advantage, as well as being an appealing choice when the transformation itself is known or suspected to be comprised of random (and possibly independent) positive increments in y and x. In such cases smooth representation such as polynominals, power series, or continuous orthogonal functions are generally found to be less adequate, as well as more difficult to manage computationally.

When a more computationally exhaustive search is contemplated, the use of piecewise linear approximation enjoys the additional advantage of being a suitable basis for uniform approximation of continuous functions of bounded variation. Therefore, it appears to be a logical choice for approximating a monotone continuous function. In this case, the form assumed by the relevant probability functional will also be seen to have the further computational advantage of enabling direct hypothesis testing on the choice of intervals employed in constructing the piecewise linear approximation. This allows at least the potential for dealing with what is usually the most disadvantageous aspect of piecewise linear approximation--namely, the choice of node points of a discontinous derivative.

The basic procedure advocated in this presentation is the application of the principle of maximum likelihood to the simultaneous estimation of the nonlinear map and the statistics (in the Gaussian case) of the underlying process. This estimator will be seen to embody a criterion of optimality that arises from the theoretical analysis of the effect of instantaneous nonlinear transformation in the Gaussian case.

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